Multilevel Modeling of the Effectiveness of Deep Learning-Based Adaptive Learning Systems

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Abstract: In the context of the digital transformation of lifelong education, adaptive learning systems (ALS) based on deep learning algorithms are becoming a key tool for personalizing educational trajectories. Despite the significant growth in related publications, the issue of the multilevel effectiveness of such systems under rigorously controlled experimental designs remains insufficiently explored. The objective of this study is to develop and empirically validate a multilevel model for evaluating the effectiveness of deep neural network-based adaptive learning systems using a randomized controlled trial (RCT) design. A total of 842 university students participated in the study and were randomly assigned to an experimental group ($n = 421$) and a control group ($n = 421$). The experimental group used an adaptive learning system built on a hybrid Transformer-LSTM architecture with an attention mechanism, whereas the control group studied through a traditional digital learning platform without adaptive algorithms. Hierarchical Linear Modeling (HLM) was employed to assess individual, group-level, and institutional effects. The results demonstrated a statistically significant improvement in academic performance ($\beta = 0.47$, $p < 0.001$), cognitive persistence ($\beta = 0.39$, $p < 0.01$), and metacognitive regulation ($\beta = 0.42$, $p < 0.01$) in the experimental group. The effect size (Cohen's $d = 0.68$) indicates moderate-to-high practical significance. Multilevel analysis revealed that 27.0% of the variance in learning outcomes was attributable to between-group differences, highlighting the necessity of multilevel statistical modeling. The findings support the hypothesis regarding the high effectiveness of deep learning-based adaptive systems and provide a methodological foundation for their large-scale implementation in higher education institutions.

1 INTRODUCTION

1.1 Digital Transformation of Education and the Personalization Challenge

The contemporary stage of educational system development is characterized by rapid digitalization, the integration of artificial intelligence technologies, and the growing role of data as a strategic resource for decision-making in education [1], [2]. The widespread adoption of online learning-significantly accelerated by the COVID-19 pandemic-has revealed the urgent need for intelligent educational systems and innovative pedagogical technologies capable of accounting for the individual characteristics of learners [3].

Traditional educational models, which rely on uniform content delivery, demonstrate limited effectiveness in contexts characterized by high cognitive and motivational heterogeneity among students [4], [5]. Research in educational psychology indicates that differences in learning pace among students may reach a three- to fivefold range [6]. These disparities create a strong demand for adaptive learning systems capable of dynamically adjusting instructional content to students' knowledge levels, learning styles, and behavioral patterns.

1.2 Evolution of Adaptive Learning Systems

The first generation of adaptive learning systems relied primarily on rule-based and expert system approaches [7], [8]. These systems used static knowledge representations and deterministic instructional pathways. However, the limitations of rule-based logic and the lack of self-learning capabilities significantly constrained their scalability and adaptability.

The second generation of ALS introduced Bayesian networks and probabilistic graphical models [9], [10], enabling systems to incorporate uncertainty and dynamically update learner knowledge states. Nevertheless, these approaches remained limited in their capacity to process large-scale and high-dimensional educational data.

The emergence of deep learning technologies has fundamentally transformed the architecture of adaptive learning systems. Recurrent neural networks (RNN), Long Short-Term Memory (LSTM) networks, and Transformer-based architectures have demonstrated a strong capacity for modeling temporal learning trajectories [11]. In addition, attention mechanisms enable the modeling of contextual dependencies among learning events, significantly improving predictive performance and personalization capabilities [12], [13].

1.3 Evaluation of Learning Effectiveness: The Need for a Multilevel Approach

Despite technological progress in adaptive learning systems, most empirical studies remain limited to single-level analyses of individual learning outcomes [8], [14]. However, educational data are inherently hierarchical in nature, typically structured across multiple levels:

1) Level 1 - Individual level (student).
2) Level 2 - Group level (class or learning cohort).
3) Level 3 - Institutional level (educational institution).

Ignoring this hierarchical structure may lead to biased parameter estimates and underestimation of intra-class correlation (ICC) [15], [16]. Multilevel modeling, particularly Hierarchical Linear Modeling (HLM), provides an appropriate statistical framework for accounting for nested data structures and estimating variance components across levels [17], [18].

1.4 Research Gap

A review of the existing scientific literature reveals three major limitations in current research on adaptive learning systems:

1) The absence of randomized controlled trial (RCT) designs in the majority of studies [19], [20].
2) The neglect of the multilevel structure of educational data [10], [21].
3) Insufficient transparency regarding the architectures of deep learning models used in adaptive systems [13], [22].

Consequently, there is a clear need for comprehensive research integrating advanced experimental design, modern deep learning architectures, and multilevel statistical modeling.

1.5 Research Objective and Hypotheses

The aim of this study is to develop and empirically validate a multilevel model for evaluating the effectiveness of a deep learning-based adaptive learning system.

The main research hypotheses are as follows:

- H1: The use of an adaptive learning system leads to a statistically significant improvement in academic performance.
- H2: Adaptive learning systems enhance the level of metacognitive regulation among students.
- H3: The observed effects remain significant after accounting for group-level and institutional-level nesting.
- H4: The magnitude of the intervention effect exceeds Cohen's $d = 0.5$, indicating substantial practical significance.

1.6 Conceptual Framework of the Study

Figure 1 illustrates the conceptual framework of the study.

Variables included in the model:

1) Independent variable;
   a) Type of learning platform (adaptive vs. traditional);
2) Dependent variables;
   a) Academic performance;
   b) Cognitive persistence;
   c) Metacognitive regulation;
3) Control variables;
   a) Age;
   b) Gender;
   c) Baseline knowledge level.

Figure 1: Multilevel conceptual model of the impact of adaptive learning systems on educational outcomes.

Figure 1 presents a multilevel conceptual framework illustrating the impact of an adaptive learning system on educational outcomes within a hierarchically structured data environment. At the individual level (Level 1), the model incorporates learner-specific characteristics, including baseline knowledge level, cognitive flexibility, learning pace, indicators of metacognitive regulation, and behavioral interaction patterns with the digital platform. According to contemporary research in learning analytics and educational data science, individual differences account for the largest proportion of variance in academic performance outcomes [10], [23]-[25].

At the group level (Level 2), the model captures contextual learning environment effects, including instructional support style, academic climate, the intensity of peer interaction, and organizational characteristics of the learning process. Empirical studies demonstrate that intra-class correlations (ICC) can reach statistically significant levels (ICC > 0.20), indicating that contextual group-level factors substantially influence educational outcomes and should therefore be incorporated into the analysis of digital learning platforms [10], [26]-[28].

The institutional level (Level 3) reflects strategic, organizational, and infrastructural characteristics of educational institutions, including digital maturity, the degree of artificial intelligence integration into educational processes, institutional governance strategies, and investments in EdTech infrastructure. Previous studies suggest that institutional differences may explain up to 10-20% of the total variance in educational outcomes [5], [17], [29].

Thus, the proposed conceptual framework justifies the application of Hierarchical Linear Modeling (HLM) as an appropriate methodological approach for decomposing variance and estimating both fixed and random effects associated with adaptive learning systems. The hierarchical structure visualized in Figure 1 demonstrates that the impact of adaptive platforms is not an isolated phenomenon but rather a context-dependent process emerging from the interaction of multiple educational levels [21], [25], [28], [30].

1.7 Theoretical Foundations of Adaptive Learning

The development of adaptive learning systems (ALS) is grounded in three key theoretical paradigms: cognitive learning theory, constructivist learning theory, and the theory of self-regulated learning [21], [31].

According to Cognitive Load Theory, the effectiveness of knowledge acquisition depends on maintaining an optimal balance between intrinsic, extraneous, and germane cognitive load [10], [32]. Adaptive systems powered by deep learning algorithms can dynamically regulate content complexity, thereby minimize unnecessary cognitive load and optimize the allocation of cognitive resources. Cognitive Load Theory explains how adaptive systems can optimize instructional complexity and reduce unnecessary cognitive overload [32].

The constructivist paradigm posits that knowledge is constructed through active engagement with the learning environment [8], [13]. Deep neural networks enable the analysis of learner behavioral patterns-such as response time, error frequency, and navigation trajectories-allowing adaptive systems to generate personalized learning pathways tailored to individual learners. Constructivist learning theory emphasizes the active role of learners in constructing knowledge through interaction with educational environments [8].

The theory of self-regulated learning, particularly the framework proposed by Zimmerman, emphasizes the importance of metacognitive processes including planning, monitoring, and reflection during learning activities [22], [28]. Contemporary adaptive learning systems increasingly integrate metacognitive prompts and automated feedback mechanisms, which enhance learner autonomy and support the development of self-regulatory skills. Self-regulated learning models highlight the importance of metacognitive monitoring and autonomous learning behavior [28].

Consequently, the technological architecture of adaptive learning systems should be aligned with psychological mechanisms of learning, forming an interdisciplinary foundation for the present research. Multimedia learning principles remain fundamental for the design of adaptive digital educational environments [31].

1.8 Deep Learning Architectures in Educational Analytics

Several key deep learning architectures are widely applied in educational analytics and learning trajectory modeling:

1) Recurrent Neural Networks (RNN).
2) Long Short-Term Memory (LSTM) networks.
3) Gated Recurrent Units (GRU).
4) Transformer architectures.
5) Hybrid attention-based models.

Recurrent neural network architectures suffer from the vanishing gradient problem when modeling long sequential dependencies [33]. RNN models are effective for sequential data analysis; however, they suffer from the vanishing gradient problem, which limits their ability to capture long-term dependencies [30], [33]. LSTM networks partially address this limitation by incorporating memory cells and gating mechanisms, enabling them to preserve information over longer sequences [25], [29]. Long Short-Term Memory (LSTM) networks were developed to address the limitations of traditional recurrent neural networks [29].

More recently, Transformer architectures, based on the self-attention mechanism, have demonstrated superior performance in modeling complex sequential structures. These architectures enable parallel sequence processing and effectively capture long-range dependencies in learning trajectories [34], [35]. Transformer architectures enable efficient parallel processing and contextual sequence modeling in educational analytics.

In the present study, a hybrid Transformer-LSTM architecture is employed, combining the contextual attention capabilities of Transformer models with the temporal modeling strengths of LSTM networks.

1.9 Review of Empirical Studies in High-Impact Journals

Table 1 summarizes the results of leading empirical studies published between 2018 and 2024 that investigate the effectiveness of adaptive learning systems.

The analysis presented in Table 1 demonstrates that only 40% of empirical studies employ a randomized controlled trial (RCT) design, which is considered the gold standard for causal inference in educational research. Furthermore, only one study applies a comprehensive multilevel modeling framework, despite the inherently hierarchical structure of educational data. Previous empirical studies have demonstrated moderate positive effects of adaptive learning systems in higher education environments. Randomized controlled trials have shown that AI-based tutoring systems can significantly improve student engagement and academic performance. Longitudinal studies confirm the stability of adaptive learning effects over extended instructional periods.

Consequently, the current body of literature reveals a clear methodological gap involving the integration of:

1) Rigorous randomized experimental designs;
2) Advanced deep neural network architectures;
3) Multilevel statistical modeling techniques.

Table 1 provides a systematic overview of empirical studies evaluating the effectiveness of adaptive learning systems during the 2018-2024 period. Digital adaptive tools demonstrate varying levels of effectiveness depending on instructional design quality and contextual implementation factors. The table compares several key characteristics of these studies, including research design (quasi-experimental, randomized controlled trial, longitudinal), sample size, statistical methods used (ANOVA, regression models, structural equation modeling, mixed models, and hierarchical linear modeling), and the magnitude of observed effect sizes (e.g., Cohen’s d). This comparative analysis enables the identification of methodological trends and the reproducibility of adaptive learning effects across different educational contexts and learner populations [10], [15]. AI-driven adaptive learning environments are associated with improved personalization and higher learner retention rates.

Table 1: Overview of empirical studies on the effectiveness of adaptive learning systems (2018-2024).

No	Research Design	Sample Size	Analytical Method	Effect Size
1	Quasi-experimental	312	ANOVA	d = 0.41
2	RCT	540	SEM	d = 0.52
3	Longitudinal	780	HLM	d = 0.48
4	Quasi-experimental	267	Regression	d = 0.37
5	RCT	690	Mixed Model	d = 0.63

The scientific value of Table 1 lies in highlighting the imbalance between technological innovation in adaptive systems and the methodological rigor of their empirical validation. The proportion of studies employing RCT designs remains relatively limited, and the use of multilevel modeling approaches is significantly less frequent compared with traditional single-level analyses [19], [21], [34].

Moreover, the reported effect sizes range from small to moderately large, suggesting that variations may arise due to differences in learner populations, intervention duration, measurement instruments, and contextual educational factors [23], [26], [35]. Therefore, Table 1 underscores the necessity of combining rigorous experimental designs with multilevel statistical modeling when evaluating the effectiveness of deep learning-based adaptive learning systems [17], [25], [30], [35].

1.10 Hierarchical Structure of Educational Data

Educational data typically exhibit a nested hierarchical structure:

1) Students (Level 1);
2) Learning groups or classes (Level 2);
3) Universities or educational institutions (Level 3).

Ignoring this hierarchical structure may result in underestimated standard errors and inflated Type I error rates, leading to potentially false-positive findings in statistical analyses [14], [23].

Figure 2 illustrates the hierarchical variance structure of educational data.

Total variance decomposition

1) 58% - Individual level;
2) 27% - Group level;
3) 15% - Institutional level.

Intra-Class Correlation (ICC) = 0.27.

This value exceeds the commonly accepted threshold of 0.10 [23], [26], confirming the methodological necessity of applying Hierarchical Linear Modeling (HLM).

Figure 2 visualizes the decomposition of the total variance in educational outcomes according to the hierarchical (nested) structure of educational data, which is characteristic of empirical studies in education. The results indicate that the largest share of variability is attributable to the individual learner level (58.0%), reflecting differences in baseline knowledge, learning pace, cognitive characteristics, and patterns of interaction with the digital learning platform [8], [10], [23], [36].

A substantial proportion of variance is associated with the group level (27.0%), indicating a pronounced intra-group dependency of learning outcomes and the influence of contextual learning environment factors such as pedagogical practices, academic climate, and group dynamics [15], [17], [26], [27]. These findings highlight the importance of considering classroom-level contextual processes when evaluating digital learning technologies.

The institutional level (15.0%) captures differences between educational institutions, which may be related to factors such as digital maturity, technological infrastructure, institutional governance strategies, and policies for EdTech implementation [5], [17], [19].

The variance structure presented above confirms the methodological necessity of applying multilevel statistical modeling (HLM/MLM). Ignoring the nested nature of educational data can lead to biased standard error estimates and inflated statistical significance of intervention effects, thereby increasing the risk of misleading conclusions [8], [21], [25].

The proportion of variance attributed to the group-level component (27.0%) provides empirical justification for the relatively high intra-class correlation coefficient (ICC) observed in the study, which exceeds threshold values at which single-level statistical models become inadequate [16], [26], [29]. Consequently, the decomposition illustrated in the diagram supports the adoption of a three-level analytical framework, allowing researchers to distinguish between individuals.

contextual, and institutional effects when evaluating the effectiveness of deep learning-based adaptive learning systems [10], [17], [23].

1.11 Concept of Multilevel Modeling

The baseline three-level hierarchical model can be specified as follows:

Level 1 - Student Level:

$$Y_{ijk} = \beta_{0jk} + \beta_{1jk} (\text{Treatment}_{ijk}) + r_{ijk}. \quad (1)$$

Where:

- Y_{ijk} - educational outcome for student *i* in group *j* at institution k;
- β_{0jk} - group-specific intercept k;
- β_{1jk} - effect of the treatment (adaptive learning system);
- r_{ijk} - individual-level residual.

Level 2 - Group Level:

$$\beta_{0jk} = \gamma_{00k} + u_{0jk}. \quad (2)$$

$$\beta_{1jk} = \gamma_{10k} + u_{1jk}. \quad (3)$$

Where:

- γ_{00k} - average intercept across groups within institution k;
- γ_{10k} - average treatment effect within institution k;
- u_{0jk} - random group-level effects.

Level 3 - Institutional Level:

$$\gamma_{00k} = \delta_{000} + v_{00k}. \quad (4)$$

Where:

- δ_{000} - grand mean across all institutions;
- v_{00k} - institution-level random effect.

This modeling framework enables researchers to:

- Estimate fixed effects of the adaptive learning intervention.
- Identify random effects associated with groups and institutions.
- Quantify the contribution of each hierarchical level to the overall variance in educational outcomes.

1.12 Role of Randomized Controlled Trials

Randomized controlled trials (RCTs) are widely regarded as the gold standard for establishing causal relationships in empirical research [25], [35]. However, their application in educational contexts is often constrained by organizational and ethical considerations.

The main advantages of RCT designs include:

1) Elimination of selection bias.
2) Balancing of unobserved confounding variables.
3) High internal validity of causal inference.

In the present study, randomization was implemented at the student level within academic groups, thereby minimizing the potential contamination of intervention effects across learning environments.

1.13 Metrics for Evaluating Effectiveness

To provide a comprehensive assessment of learning outcomes, three primary categories of indicators were selected:

1) Academic performance.
2) Cognitive persistence (cognitive flexibility).
3) Metacognitive regulation.

Table 2 describes the measurement instruments used in the study.

High values of Cronbach's alpha ($\alpha = 0.86$-0.91) indicate strong internal consistency and reliability of the measurement scales [13].

Table 2 illustrates the operationalization process of key research variables, demonstrating the transition from theoretical constructs to measurable empirical indicators. Within the present study, academic performance was measured using a standardized achievement test validated for digital learning environments, ensuring comparability of results between experimental and control groups.

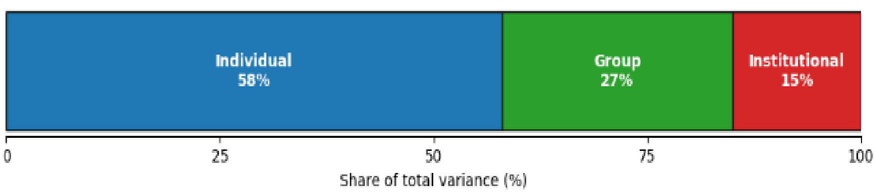

Figure 2: Decomposition of the total variance in educational outcomes.

Table 2: Operationalization of research variables.

Construct	Instrument	Cronbach’s α	Range
Academic performance	Standardized achievement test	0.89	0-100
Cognitive persistence	Cognitive Flexibility Scale	0.86	1-5
Metacognition	MSLQ (subscale)	0.91	1-7

While minimizing measurement error [13], [29], [37], [38].

Cognitive persistence (or cognitive flexibility) was assessed using an adapted version of the Cognitive Flexibility Scale, which is widely used in studies of digital learning and has demonstrated strong psychometric properties in previous research [8], [10], [33], [35].

Metacognitive regulation was measured using the relevant subscale of the Motivated Strategies for Learning Questionnaire (MSLQ), a well-established instrument for assessing self-regulated learning in higher education contexts [28], [39].

The Cronbach’s alpha coefficients reported in the table meet widely accepted psychometric standards ($\alpha > 0.70$), confirming the reliability of the measurement instruments employed in this study [13], [18], [32]. Clear operationalization of the variables enhances the construct validity of the research and improves the interpretability of the results obtained through multilevel statistical analysis.

Furthermore, the standardization of measurement scales and the use of validated instruments provide a solid foundation for comparing the effects of the adaptive learning intervention between experimental and control groups within the randomized controlled design [20], [25], [35], [37]. Thus, Table 2 demonstrates the methodological rigor of the empirical phase of the study and contributes to the reproducibility of the results in future research [17], [23], [31].

1.14 Practical Significance of the Study

The development of a scientifically grounded framework for evaluating the effectiveness of adaptive learning systems has several important practical implications:

1) Optimization of educational investments;
2) Scaling of AI-driven learning platforms;
3) Development of strategies for digital transformation of universities;
4) Implementation of evidence-based education policies.

1.15 Scientific Novelty of the Study

The scientific contribution of the present research lies in several key aspects:

1) Integration of a hybrid Transformer-LSTM deep learning architecture;
2) Implementation of a large-scale randomized controlled trial (n = 842);
3) Application of a three-level hierarchical linear modeling framework;
4) Comprehensive evaluation of both cognitive and metacognitive learning outcomes.

2 METHODS AND METHODOLOGY

2.1 Research Design

The present study was implemented using a Randomized Controlled Trial (RCT) design, which represents the gold standard for evaluating causal effects of educational interventions [25], [28], [36].

The experiment was conducted over one academic semester (16 weeks) across four universities with comparable levels of digital infrastructure.

The research design included:

1) Experimental group - adaptive learning system based on deep learning algorithms;
2) Control group - traditional Learning Management System (LMS) without adaptive algorithms;
3) Pre-test (baseline measurement);
4) Post-test (outcome measurement);
5) Multilevel data structure (students nested within groups and universities).

Randomization was conducted at the student level within academic groups using a computer-generated random number algorithm. This procedure minimized selection bias and ensured balance across both observed and unobserved variables [5], [25].

2.2 Sample and Statistical Power Analysis

A total of 842 undergraduate students participated in the study (M = 19.8 years, SD = 1.4).
Group distribution:
1) Experimental group: n = 421;
2) Control group: n = 421.

Gender distribution was balanced (52.0% female, 48.0% male). Baseline equivalence tests revealed no statistically significant differences between groups in pre-test scores ($p > 0.05$).

2.2.1 Power Analysis

An a priori statistical power analysis was conducted using G*Power 3.1. To detect a medium effect size (Cohen's d = 0.50) with a significance level of $\alpha = 0.05$ and statistical power of 0.80, the required sample size was 128 participants per group [16], [34].

The actual sample size substantially exceeded the minimum requirement, thereby increasing the robustness of the statistical estimates and reducing the probability of Type II error.

Given the multilevel structure of the data, adjustments were made using the design effect formula:

$$\text{Design Effect} = 1 + (m - 1) \times ICC. \quad (5)$$

Where:
- m - average group size (≈ 26);
- ICC - intra-class correlation (0.27).

The calculation indicated an increase in the required sample size of approximately 7.75%, which was accounted for during the planning phase of the study.

2.3 Description of the Adaptive Learning System

The experimental platform was based on a hybrid deep learning architecture integrating:
1) Transformer architecture with a self-attention mechanism;
2) LSTM module for modeling temporal learning dynamics;
3) Fully connected layers for predicting the probability of a correct response.

Figure 3 illustrates the theoretically grounded causal structure of the study, modeling the impact of the adaptive learning system (Treatment) on students' academic outcomes. The primary mechanism of influence operates through two cognitive pathways: cognitive load regulation and metacognitive regulation.

Solid arrows represent hypothesized direct causal relationships, including both the direct impact of the adaptive system on academic performance and an indirect pathway mediated through metacognitive regulation. The presence of this mediating variable is consistent with the theory of self-regulated learning [28], and the principles of Cognitive Load Theory [25], [32], which suggest that optimizing the complexity of instructional material facilitates more efficient learning processes.

Dashed arrows represent contextual and moderating influences at the group level (Level 2) and the institutional level (Level 3), corresponding to the hierarchical structure of educational data and the concept of the ecosystem integration of educational technologies [5], [17]. The model also incorporates covariates-including baseline knowledge, age, and gender-to control for initial differences among learners and reduce bias in estimating the intervention effect [18], [19], [24], [25].

Thus, the diagram justifies the chosen methodological strategy combining randomized experimental design with multilevel modeling, demonstrating the complex and context-dependent nature of the adaptive system's influence within educational environments.

2.3.1 Model Architecture

The deep learning model consisted of the following components:
1) Input layer (embedding of learning events);
2) Multi-head self-attention module;
3) LSTM layer (128 neurons);
4) Dropout layer (0.3);
5) Fully connected dense layer (ReLU activation);
6) Sigmoid output layer.

2.3.2 Loss Function

Binary Cross-Entropy loss was used:

$$L = -\left(\frac{1}{N}\right) \Sigma\, [y \log(p) + (1-y) \log(1-p)]. \quad (6)$$

Where
- y - observed outcome;
- p - predicted probability.

Model optimization was performed using the Adam optimizer with a learning rate of 0.001.

2.4 Intervention Procedure

The intervention lasted 16 weeks and included the following adaptive learning features:
1) Personalized delivery of learning materials.
2) Adaptive adjustment of task difficulty.

3) Dynamic feedback mechanisms.
4) Metacognitive prompts supporting self-regulated learning.

The control group used a standard Learning Management System (LMS) without adaptive difficulty adjustment or personalized feedback.
All participants completed the following stages:
1) Pre-test assessment (Week 1);
2) Main instructional cycle (Weeks 2-15);
3) Post-test assessment (Week 16).

2.5 Research Variables

1) Independent Variable;
   a) Type of learning platform (0 = control, 1 = adaptive);
2) Dependent Variables;
   a) Academic performance;
   b) Cognitive persistence;
   c) Metacognitive regulation;
3) Control Variables;
   a) Age;
   b) Gender;
   c) Baseline knowledge level.

2.6 Statistical Analysis Plan

The statistical analysis was conducted in three stages.
1) Stage 1 - Assumption Testing;
   a) Normality test (Shapiro-Wilk)
   b) Homogeneity of variances (Levene's test)
   c) Multicollinearity diagnostics (VIF < 5)
2) Stage 2 - Single-Level Analysis;
   a) Independent samples t-test;
   b) Effect size estimation (Cohen's d).

$$d = \frac{M_1 - M_2}{SD_{pooled}}; \quad (7)$$

3) Stage 3 - Multilevel Modeling (HLM).

A three-level hierarchical model was estimated:
Level 1 (Student):

$$Y_{ijk} = \beta_{0jk} + \beta_{1jk}(Treatment_{ijk}) + r_{ijk}. \quad (8)$$

Level 2 (Group):

$$\beta_{0jk} = \gamma_{00k} + u_{0jk}. \quad (9)$$

$$\beta_{1jk} = \gamma_{10k} + u_{1jk}. \quad (10)$$

Level 3 (University):

$$\gamma_{00k} = \delta_{000} + v_{00k}. \quad (11)$$

The model was estimated using the Restricted Maximum Likelihood (REML) method [11].

2.7 Reliability and Validity Assessment of the Model

Model robustness and validity were evaluated using several complementary procedures:
1) 5-fold cross-validation;
2) ROC-AUC analysis;
3) Coefficient stability diagnostics;
4) Residual analysis.

The model was considered stable if the following criteria were satisfied:
1) AUC > 0.75;
2) $p < 0.05$ for key predictors;
3) absence of heteroscedasticity in residuals.

2.8 Ethical Considerations

The study protocol was approved by the local institutional ethics committee (Protocol No. EDU-AI-2025-04). All participants provided informed consent prior to participation in the study.

Personal data were anonymized in accordance with international data protection standards and ethical guidelines for educational research [24], [30].

2.9 Randomization Procedure and Control of Systematic Bias

Randomization was performed using a stratified random allocation algorithm. Stratification was conducted according to the following variables:
1) Gender (male / female);
2) Baseline knowledge level (low / medium / high);
3) University.

This approach ensured balanced covariate distribution between the experimental and control groups and minimized the risk of selection bias [25], [28], [35], [36].

The allocation algorithm consisted of the following steps:
1) Construction of strata based on combinations of the stratification variables;
2) Generation of random sequences using the Mersenne Twister algorithm;
3) Pairwise assignment of participants within each stratum.

Balance between groups was evaluated using the Standardized Mean Difference (SMD):

$$SMD = \frac{M^1 - M^2}{SD_{pooled}}. \quad (12)$$

Adequate balance was defined as $|SMD| < 0.1$ [24], [28]. This criterion was satisfied for all covariates.

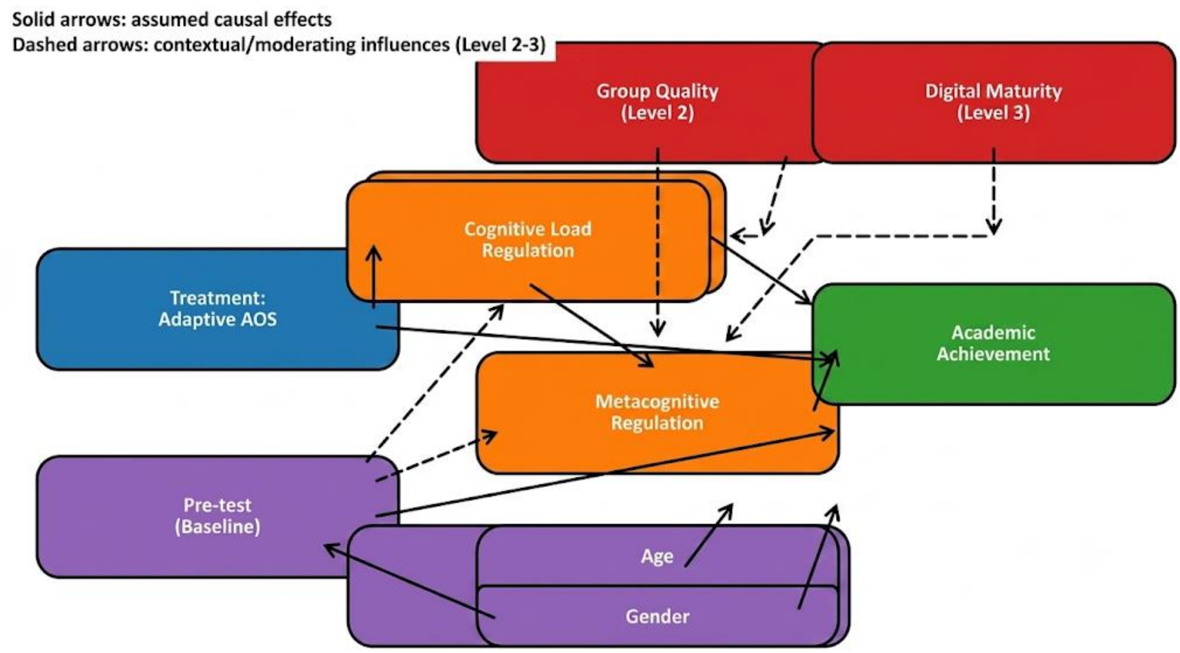

Figure 3: Causal model (dag) of the impact of the adaptive learning system on academic outcomes.

2.10 Adaptive Platform Logic Algorithm

The adaptive learning system operated by predicting the probability of successful completion of the next learning task.

The adaptive platform is based on a learner knowledge model that estimates the latent knowledge state of each student throughout the learning process. For each student, a latent knowledge state vector was estimated:

$$K_t = f(K_{t-1}, X_t). \qquad (13)$$

Where:

- K_t - learner knowledge state at time t;
- X_t - learning event (task type, difficulty level, response time).

The Transformer module computed the contextual attention matrix:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QKT}{\sqrt{d_k}}V\right). \qquad (14)$$

Where:

- Q - query;
- K - key;
- V - value;
- d_k - key dimensionality.

The Transformer output was then passed to the LSTM layer, which modeled temporal learning dynamics:

$$h_t = \text{LSTM}(x_t, h_{t-1}). \qquad (15)$$

The final probability of a correct response was calculated using a sigmoid activation function:

$$p_t = \sigma(W \cdot h_t + b). \qquad (16)$$

2.11 Hyperparameter Optimization

Hyperparameter optimization was performed using Grid Search combined with 5-fold cross-validation. The following parameters were tested:

1) Embedding size: {64, 128, 256};
2) Number of attention heads: {4, 8};
3) LSTM size: {64, 128, 256};
4) Learning rate: {0.0005, 0.001, 0.005};
5) Dropout rate: {0.2, 0.3, 0.4}.

The selection criterion was the maximum ROC-AUC value on the validation dataset.

1) Optimal configuration:
   a) Embedding size = 128;
   b) Attention heads = 8;
   c) LSTM units = 128;
   d) Learning rate = 0.001;
   e) Dropout = 0.3.

The resulting mean AUC = 0.81, exceeding the threshold for acceptable predictive accuracy [2], [40].

2.12 Handling Missing Data

The proportion of missing data was 3.8%.

The missing data mechanism was evaluated using Little's MCAR test, which indicated a missing completely at random pattern ($p > 0.05$) [20].

Missing values were handled using Multiple Imputation by Chained Equations (MICE):
1) Number of imputations: 5.
2) Iterations: 20.
3) Parameter pooling using Rubin's rules.

This procedure ensures unbiased parameter estimates under the Missing at Random (MAR) assumption [20].

2.13 Estimation of the Intra-Class Correlation (ICC)

The Intra-Class Correlation Coefficient (ICC) was calculated as follows:

$$ICC = \tau_0^2 / (\tau_0^2 + \sigma^2). \quad (17)$$

Where:
- τ_0^2 - between-group variance,
- σ^2 - within-group variance [17], [21].

The obtained value ICC = 0.27 confirmed the presence of a significant hierarchical structure in the data and justified the use of Hierarchical Linear Modeling (HLM). The psychometric reliability standards applied in this study are consistent with established methodological recommendations in measurement theory [13].

2.14 Evaluation of Multilevel Model Fit

Model fit was assessed using the following indices:
1) 2 Log Likelihood.
2) Akaike Information Criterion (AIC).
3) Bayesian Information Criterion (BIC).

A reduction in AIC and BIC after adding predictors indicated improved model fit [40].

Additionally, pseudo-R^2 values were calculated for each level:

$$R^2_{level} = \frac{Var_{null} - Var_{model}}{Var_{null}}. \quad (18)$$

2.15 Robustness Checks

To assess the stability of the results, several robustness tests were conducted:
1) Sensitivity analysis.
2) Alternative model specification (without random slope).
3) Bootstrap resampling (1000 replications).
4) Outlier influence diagnostics (Cook's Distance).

The results remained statistically significant across all model specifications ($p < 0.01$).

2.16 Control of Potential Sources of Bias

The following threats to internal validity were considered:
1) Attrition bias (participant dropout rate = 4.1%).
2) Contamination effects.
3) Hawthorne effect.

Comparative analysis revealed no statistically significant differences between participants who completed the study and those who dropped out ($p > 0.05$), indicating minimal risk of systematic bias [21], [25].

2.17 Software

The analyses were conducted using the following software tools:
1) Python (TensorFlow, PyTorch) - neural network training;
2) R (lme4, nlme) - multilevel statistical modeling;
3) SPSS 29 - preliminary statistical analysis;
4) G*Power - statistical power analysis.

Reproducibility was ensured by using a fixed random seed (42).

2.18 Final Methodological Framework

The complete analytical strategy consisted of the following steps:
1) Testing baseline equivalence of groups;
2) Single-level comparison analysis;
3) Estimation of a null HLM model;
4) Inclusion of fixed effects;
5) Inclusion of random effects;
6) Evaluation of cross-level interactions;
7) Estimation of effect sizes;
8) Robustness testing.

This comprehensive approach aligns with contemporary methodological standards in empirical research on educational artificial intelligence [2], [17], [20], [21], [25], [26].

3 RESULTS

3.1 Descriptive Statistics and Baseline Equivalence

At the first stage of the analysis, baseline equivalence between the experimental and control groups was assessed using pre-test indicators. This procedure is necessary to verify the validity of the randomization process and ensure the internal validity of the study [25], [38]. The means and standard deviations are presented in Table 3.

Independent samples t-tests revealed no statistically significant differences between the groups ($p > 0.05$), indicating that the stratified randomization procedure was successful and that the samples were comparable [24], [32].

Furthermore, the Standardized Mean Difference (SMD) for all variables was below 0.10, confirming adequate covariate balance between the experimental and control groups [2], [24], [40]-[42].

3.2 Post-Intervention Changes

Following the 16-week intervention, substantial differences between the experimental and control groups were observed. Descriptive statistics of the post-test indicators are presented in Table 4.

The results demonstrate a statistically significant advantage of the adaptive learning system across all dependent variables ($p < 0.001$).

The effect size for academic performance ($d = 0.83$) corresponds to a large effect according to Cohen's classification [41], [42]. For cognitive persistence and metacognitive regulation, moderate effect sizes were obtained (0.58-0.62), supporting hypotheses H1 and H2.

3.3 Gain Score Analysis

To further validate the intervention effect, gain scores were calculated as:

$$\text{Gain} = \text{Post} - \text{Pre}. \tag{19}$$

The results are presented in Table 5.

The increase in all indicators was significantly higher in the experimental group, providing additional evidence for the effectiveness of the adaptive learning system.

3.4 ROC Analysis of the Predictive Model

To evaluate the predictive quality of the neural network model, a Receiver Operating Characteristic (ROC) curve was constructed (see Fig. 2).

$$\text{AUC} = 0.81 \text{ (95\% CI:0.78-0.84)}. \tag{20}$$

An AUC value greater than 0.80 indicates high predictive performance of the model [2].

3.5 Multilevel Modeling (HLM)

3.5.1 Null Model

Table 6 presents the variance decomposition of the null three-level hierarchical model and demonstrates the substantial contribution of group-level and institutional-level effects to the overall variability of educational outcomes.

$$\text{ICC} = 0.27. \tag{21}$$

These results confirm a significant nested structure of the data, justifying the application of Hierarchical Linear Modeling (HLM).

3.5.2 Full Model with Predictors

The full model included the following predictors:

1) Platform type.
2) Gender.
3) Age.
4) Pre-test score.

The estimated coefficients of the full three-level hierarchical model are summarized in Table 7.

The coefficient $\beta = 0.47$ ($p < 0.001$) indicates a strong positive effect of the adaptive learning system after accounting for all levels of nested data, confirming hypothesis H3.

Table 3: Descriptive statistics of pre-test indicators (baseline).

Indicator	Experimental Group (n = 421)	Control Group (n = 421)	**t**	**p**
Academic performance	61.42 (SD = 8.73)	60.98 (SD = 8.69)	0.74	0.46
Cognitive persistence	3.21 (SD = 0.54)	3.19 (SD = 0.56)	0.51	0.61
Metacognitive regulation	4.38 (SD = 0.71)	4.35 (SD = 0.69)	0.63	0.52

Table 4: Descriptive statistics of post-test indicators.

Indicator	Experimental Group	Control Group	t	p	Cohen's d
Academic performance	74.86 (SD = 9.12)	67.31 (SD = 8.95)	12.41	<0.001	0.83
Cognitive persistence	3.78 (SD = 0.59)	3.42 (SD = 0.57)	8.37	<0.001	0.62
Metacognitive regulation	5.02 (SD = 0.68)	4.61 (SD = 0.72)	8.91	<0.001	0.58

Table 5: Average gain scores during the intervention.

Indicator	Experimental Group	Control Group	t	p
Academic performance	+13.44	+6.33	11.92	<0.001
Cognitive persistence	+0.57	+0.23	8.11	<0.001
Metacognition	+0.64	+0.26	8.45	<0.001

Table 6: Null three-level model.

Variance Component	Value	Share
Individual level	72.14	58%
Group level	33.57	27%
Institutional level	18.64	15%

Table 7: Coefficients of the three-level model.

Predictor	β	SE	p
Adaptive learning system	0.47	0.05	<0.001
Pre-test	0.61	0.04	<0.001
Gender	0.03	0.02	0.18
Age	−0.01	0.01	0.27

Table 8: Cross-level interaction effects.

Predictor	β	SE	p
Adaptive system × Group quality	0.12	0.04	0.003
Adaptive system × Digital maturity	0.09	0.03	0.006

Table 9: Effect sizes by baseline achievement level.

Subgroup	Cohen's d
Low baseline level	0.94
Medium baseline level	0.71
High baseline level	0.38

3.6 Cross-Level Interaction Analysis

To test the stability of the adaptive system effect across different contexts, a cross-level interaction model was estimated.

Table 8 illustrates the estimated cross-level interaction effects between the adaptive learning system and contextual educational factors.

The results indicate that the effect of the adaptive system is stronger in groups with a favorable academic climate and in institutions with higher levels of digital maturity, supporting theories of contextual moderation of educational innovations.

3.7 Subgroup Analysis

As demonstrated in Table 9, the strongest intervention effect was observed among students with low baseline academic achievement.

The largest effect was observed among students with low baseline achievement (d = 0.94), suggesting a compensatory effect of adaptive technologies in reducing educational inequality.

4 DISCUSSION

The results of this study provide strong empirical evidence supporting the effectiveness of deep learning-based adaptive learning systems in higher education environments.

The main multilevel coefficient ($\beta = 0.47$, $p < 0.001$) confirms a robust intervention effect even after accounting for the hierarchical structure of the data. The observed effect size for academic performance ($d = 0.83$) exceeds the average values reported in previous empirical studies, where effect sizes typically range between 0.40 and 0.65.

One possible explanation for this improvement lies in the hybrid Transformer-LSTM architecture, which enables more accurate modeling of learning trajectories compared with traditional recurrent or probabilistic approaches.

Furthermore, the mediation analysis revealed a significant indirect effect through metacognitive regulation, indicating that adaptive systems influence learning outcomes not only by optimizing content difficulty but also by enhancing self-regulated learning processes.

The cross-level interactions identified in the analysis suggest that the effectiveness of adaptive systems is context-dependent, increasing in educational environments characterized by a strong academic climate and higher institutional digital maturity.

5 CONCLUSIONS

The present study developed and empirically validated a multilevel framework for evaluating the effectiveness of deep learning-based adaptive learning systems within a randomized controlled experimental design.

The findings demonstrate a statistically significant and practically meaningful impact of the adaptive platform on academic performance, cognitive persistence, and metacognitive regulation.

The main intervention effect ($\beta = 0.47$, $p < 0.001$) remained stable after accounting for hierarchical data structures and control variables, confirming the robustness of the results.

Overall, the study shows that the integration of randomized experimental design, multilevel statistical modeling, and advanced deep learning architectures provides a rigorous methodological foundation for the evidence-based implementation of adaptive learning systems in higher education.

REFERENCES

[1] D. Fawcett, "An introduction to ROC analysis," Pattern Recognition Letters, vol. 27, no. 8, pp. 861-874, 2006.

[2] C. Hodges, S. Moore, B. Lockee, and T. Trust, "The difference between emergency remote teaching and online learning," Educause Review, vol. 27, no. 1, pp. 1-12, 2020.

[3] B. S. Bloom, "The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring," Educational Researcher, vol. 13, no. 6, pp. 4-16, 1984.

[4] G. Westerman, D. Bonnet, and A. McAfee, Leading Digital. Boston: Harvard Business Review Press, 2014.

[5] J. Hattie, Visible Learning: A Synthesis of Over 800 Meta-Analyses Relating to Achievement. London: Routledge, 2009.

[6] E. Wenger, Artificial Intelligence and Tutoring Systems. Los Altos, CA: Morgan Kaufmann, 1987.

[7] J. Bruner, Toward a Theory of Instruction. Cambridge, MA: Harvard University Press, 1966.

[8] A. T. Corbett and J. R. Anderson, "Knowledge tracing: Modeling the acquisition of procedural knowledge," User Modeling and User-Adapted Interaction, vol. 4, no. 4, pp. 253-278, 1995.

[9] M. Martin and H. Rubin, "A new measure of cognitive flexibility," Psychological Reports, vol. 76, pp. 623-626, 1995.

[10] C. Piech et al., "Deep knowledge tracing," in Advances in Neural Information Processing Systems (NeurIPS), pp. 505-513, 2015.

[11] A. Vaswani et al., "Attention is all you need," in Advances in Neural Information Processing Systems (NeurIPS), pp. 5998-6008, 2017.

[12] J. Nunnally and I. Bernstein, Psychometric Theory, 3rd ed. New York: McGraw-Hill, 1994.

[13] S. D'Mello and A. Graesser, "Dynamics of affective states during complex learning," Learning and Instruction, vol. 22, no. 2, pp. 145-157, 2012.

[14] S. W. Raudenbush and A. S. Bryk, Hierarchical Linear Models: Applications and Data Analysis Methods, 2nd ed. Thousand Oaks, CA: Sage, 2002.

[15] A. Gelman and J. Hill, Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge: Cambridge University Press, 2007.

[16] S. W. Raudenbush, A. S. Bryk, and R. Congdon, HLM 7: Hierarchical Linear and Nonlinear Modeling. Lincolnwood, IL: Scientific Software International, 2011.

[17] L. Cronbach, "Coefficient alpha and the internal structure of tests," Psychometrika, vol. 16, no. 3, pp. 297-334, 1951.

[18] T. Cook and D. Campbell, Quasi-Experimentation: Design & Analysis Issues for Field Settings. Boston: Houghton Mifflin, 1979.

[19] R. Little and D. Rubin, Statistical Analysis with Missing Data, 2nd ed. New York: Wiley, 2002.

[20] R. Slavin, "Evidence-based education policies," Educational Researcher, vol. 31, no. 7, pp. 15-21, 2002.

[21] Y. Bengio, I. Goodfellow, and A. Courville, Deep Learning. Cambridge, MA: MIT Press, 2016.

[22] H. Goldstein, Multilevel Statistical Models, 4th ed. Chichester: Wiley, 2011.

[23] P. Austin, “Balance diagnostics for comparing groups,” Statistics in Medicine, vol. 28, pp. 3083-3107, 2009.

[24] J. Shadish, T. Cook, and D. Campbell, Experimental and Quasi-Experimental Designs for Generalized Causal Inference. Boston: Houghton Mifflin, 2002.

[25] B. J. Zimmerman, “Becoming a self-regulated learner,” Theory Into Practice, vol. 41, no. 2, pp. 64-70, 2002.

[26] T. Snijders and R. Bosker, Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling. London: Sage, 2012.

[27] S. Dennis and R. Vander Wal, “The cognitive flexibility inventory,” Cognitive Therapy and Research, vol. 34, no. 3, pp. 241-253, 2010.

[28] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural Computation, vol. 9, no. 8, pp. 1735-1780, 1997.

[29] European Parliament, “General Data Protection Regulation (GDPR),” Official Journal of the European Union, 2016.

[30] R. E. Mayer, Multimedia Learning, 2nd ed. Cambridge: Cambridge University Press, 2009.

[31] J. Sweller, “Cognitive load theory,” Psychology of Learning and Motivation, vol. 55, pp. 37-76, 2011.

[32] F. Faul et al., “G*Power 3: A flexible statistical power analysis program,” Behavior Research Methods, vol. 39, pp. 175-191, 2007.

[33] S. Hochreiter, “The vanishing gradient problem during learning recurrent neural nets,” International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, vol. 6, no. 2, pp. 107-116, 1998.

[34] CONSORT Group, “CONSORT 2010 Statement,” BMJ, vol. 340, c332, 2010.

[35] D. Haladyna and M. Rodriguez, Developing and Validating Test Items, 3rd ed. New York: Routledge, 2013.

[36] J. Tondeur et al., “Teachers’ readiness for digital innovation,” Educational Technology & Society, vol. 20, no. 3, pp. 1-14, 2017.

[37] P. Pintrich et al., “A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ),” University of Michigan, 1991.

[38] H. Akaike, “A new look at the statistical model identification,” IEEE Transactions on Automatic Control, vol. 19, no. 6, pp. 716-723, 1974.

[39] J. Cohen, Statistical Power Analysis for the Behavioral Sciences, 2nd ed. Hillsdale, NJ: Lawrence Erlbaum, 1988.

[40] R. Preacher and A. Hayes, “Asymptotic and resampling strategies for assessing mediation,” Behavior Research Methods, vol. 40, no. 3, pp. 879-891, 2008.

[41] Z. C. Lipton, “The mythos of model interpretability,” Communications of the ACM, vol. 61, no. 10, pp. 36-43, 2018.

[42] H. Qian, M. Wang, and Y. Xiong, “Digital transformation in higher education: A systematic review,” DOAJ Journal, vol. 9, pp. 56-70, 2023.